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BEARING LIFE PREDICTION MODEL FOR ELECTROMECHANICAL EQUIPMENT BY INTEGRATING DEEP NEURAL NETWORK AND K-NEAREST NEIGHBOR ALGORITHM AND ITS APPLICATION

Yiming Ma
Jilin Jianzhu University, Changchun, China
e-mail: mayiming0131@163.com

Current life prediction methods of Electromechanical equipment bearings have issues of low accuracy and lack of stability. To address these problems, firstly, indicators based on life degradation characteristics of bearings are selected. Then, a deep neural network-based life prediction model is constructed. Finally, the K-nearest neighbor algorithm is introduced to correct the deviation of the deep neural network prediction model, and a hybrid life prediction model is designed. Results show that effectiveness of the designed model was better, which was of great practical significance for detecting bearing failures in advance, reducing equipment losses and improving equipment reliability.

Keywords: bearings, deep neural network, K-nearest neighbor algorithm, deviation, life prediction model

1. Introduction

In recent years, electromechanical equipment plays a vital role in the modern industrial production. And one of the most common problems in equipment failure is life prediction of bearings. As an important part of electromechanical equipment, accurate prediction of the state of bearings is critical for normal operation and maintenance of the equipment. Traditional bearing life prediction methods mainly rely on empirical models and mathematical statistical methods, which can provide reliable prediction results in some cases, but have certain limitations in complex working conditions and variable environments (Zhang *et al.*, 2023). Deep Neural Network (DNN) is a multi-layer neuron based artificial intelligence model that can automatically extract features and perform complex pattern recognition by learning a large amount of data. It has powerful nonlinear modeling capability and high adaptivity, and is proper for processing high dimensional, nonlinear and large-scale data (Abdou, 2022). The K-Nearest Neighbors (KNN) algorithm, on the other hand, is a machine learning method that makes predictions by calculating the distances between samples and using information from the nearest neighbor samples. The algorithm is simple and effective, and has a good ability to handle small samples and nonlinear problems (Hatem, 2022). In this context, DNN and KNN are fused to design a DNN-KNN-based bearing life prediction model. Firstly, the indexes are selected with characteristics of bearing life degradation, then the remaining life prediction model is constructed by DNN, and finally KNN is introduced to correct the deviation of the model to improve the accuracy and stability of the prediction. The research is composed of five parts. The first section is the background of bearing life prediction. The second section is a review of the current research status of bearing life prediction. The third section is the construction of a bearing life prediction model, which includes three sections: index selection, model construction, and model optimization. The fourth part is the experimental outcome of the model, in which the first and the second sections are the performance and application effect analysis of the designed algorithm. The fifth section is the summary of the whole paper and shortcomings of the study.

2. Literature review

With the increasing importance of electromechanical equipment in the industrial production and life, bearing, as a core component of electromechanical equipment, its life prediction is of great significance for the operational stability and economic benefits of the equipment. In the field of bearing life prediction of electromechanical equipment, many scholars and researchers have proposed various methods and models to solve this problem. Nistane (2024) designed a rolling bearing remaining life optimization prediction model based on integrated optimization health indicators and hybrid machine learning algorithms to understand the degree of deterioration of rolling element bearings at any time. The model preprocesses the original signal data through wavelet transform and optimizes features using machine learning techniques. The results show that the prediction error of the model is low. Li and Wang (2024) designed a method that integrates time series window features and first prediction time recognition to predict the remaining life of rolling bearings using limited data. The method uses a multi-step rolling prediction strategy based on the first prediction time degradation factor to reveal the future degradation trend of bearings, and the results show a prediction error as low as 8.06%. Fei *et al.* (2024) have designed a life prediction method based on convolutional deep neural networks to improve the accuracy of turbocharger bearing life prediction. The method uses convolutional neural networks to extract feature convolutional layers and uses deep neural networks to regress and model the bearing life. The results show that this method has high efficiency and accuracy. Mao *et al.* (2019) designed a gated recurrent unit neural network for prediction of bearing life by providing sufficient feature representation and adaptive extraction for the bearing life prediction, and the findings indicated that the model had a high generalization ability and accuracy. To provide sufficient feature representation and adaptive extraction for bearing life prediction, Mao *et al.* (2019) designed a remaining life prediction method based on deep feature characterization and migration learning, which was divided into two phases to characterize the faults and correct the features to complete the prediction, and the outcomes expressed that the method had a better numerical stability and prediction accuracy. Sun *et al.* (2021) designed a method with vibration signal detection to predict the life of conventional low-voltage circuit breakers, which combined the designed signal processing method to extract effective vibration segments that characterized mechanical properties of the contact system to construct a model, and the findings illustrated that the method had a high average fit. Rezamand and other scholars determined the effect of operating conditions on the dynamics of bearing failure to achieve a hybrid prediction based on real-time monitoring and data acquisition and a vibration signal prediction method which used vibration signals to identify fault dynamics of the life of bearing prediction. A hybrid prediction method based on real-time monitoring and data acquisition and a vibration signal prediction was designed to identify the failure dynamics through vibration signals and Bayesian algorithm, which was shown to have a high prediction accuracy (Rezamand *et al.*, 2021).

To address the issue of non-existence of interpretability in bearing life prediction, Ding and other researchers designed a dynamic structure and adaptive notation method, which modeled the health indexes of multiple signals and tracked the real-time degradation of the machine by using dynamic coupling terms. The findings denoted that the method had better generalization ability and lower prediction error (Ding *et al.*, 2021). To solve the uncertainty of a recurrent neural network in predicting bearing life, Wang and other scholars designed a long and short-term memory network model based on residual convolution, which quantified the inaccuracy of prediction results by constructing an appropriate output layer obeying the normal distribution, and the findings denoted that the model could effectively predict the bearing life (Wang *et al.*, 2022). Rezamand *et al.* (2020) to accurately estimate the prediction of bearing life, designed a comprehensive prediction method based on the signal processing and adaptive Bayesian algorithm, which was based on feature extraction and feature selection. It detected, dynamics of various faults through feature extraction, feature selection and signal denoising and predicted them by using the adaptive Bayesian algorithm, and the results showed that the method had a high prediction accuracy (Rezamand *et al.*, 2020). In order to achieve accurate prediction of remaining lifespan, Wu *et al.* (2024) designed a residual lifespan prediction model based on wavelet enhanced dual tree residual network. The model decomposed time series through wavelet transform and predicted remaining lifespan by concatenating dual tree features. The results showed that the prediction effect of that method was good (Wu *et al.*, 2024). Li *et al.* (2023) researchers designed a deep adversarial network-based residual service life prediction method for partial sensor failure to achieve a good electromechanical health assessment, which extracted generalized sensor invariant features through adversarial learning to make a full use of the information from different sensors, and the findings indicated that the method had a high robustness. Yang *et al.* (2024) designed a dynamic spatiotemporal graph driven bearing remaining life prediction method based on graph data expansion to maintain normal operation of the machine. The method captured hidden information using short-time Fourier transform and predicted through a graph embedding module based on an autoencoder. The results showed that the prediction performance of that method was high (Yang *et al.*, 2024).

In summary, many scholars have made significant contributions in the field of bearing life prediction for electromechanical equipment, however, there are still some limitations of these methods, such as limited universality, missing comparative analysis and insufficient interpretability. Therefore, the study is based on life degradation characteristics of bearings for indicator selection, followed by constructing a life prediction model using DNN. At the same time, to correct the error of the DNN prediction model, the K nearest neighbor algorithm is introduced and a hybrid life prediction model is designed to improve the model performance of measurement and generalization ability.

3. Construction of the bearing life prediction model for electromechanical equipment by integrating DNN and KNN

This Section focuses on the construction of the fusion bearing life prediction model. The first section is selection of feature indicators, the second section is construction of the DNN-based model, and the third section is introduction of KNN to optimize the model.

3.1. Selection of characteristic indicators for bearing life degradation of electromechanical equipment

As a key component of electromechanical equipment, the performance degradation of bearings will seriously affect the operation safety and stability of the whole equipment. In order to effectively monitor the performance status of bearings during operation and predict their life, it is crucial to extract characteristic quantities that can reflect the performance degradation indicators of bearings (Cao *et al.*, 2023). Therefore, one needs to select the life degradation index of the bearing. In actual working conditions, there are many nonlinear factors that affect the construction performance of health indicators for rolling bearings. Traditional indicator extraction methods are prone to losing the state information on rolling bearings, and therefore cannot extract true and effective state features from complex signals. Research is being carried out on introducing deep learning models to extract state indicators of bearings. The index extraction process is shown in Fig. 1.

In the operation of electromechanical equipment, the rolling bearing as a key support component. During its long time operation, due to the influence of various factors, there may be faults or an abnormal operation state. At that time, the vibration signal will be manifested out of the bearing running state corresponding to the characteristic quantity. These characteristics

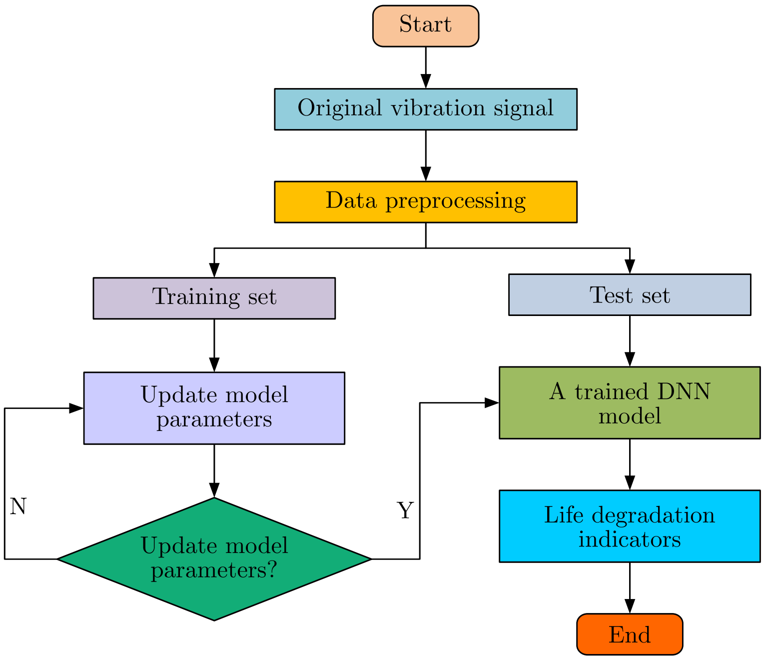

Fig. 1. Extraction process of bearing life degradation indicators

include time-domain features such as the mean value, peak value, RMS, craggyness, etc., as well as frequency-domain features such as center frequency, average energy, spectral partitioning and summation. In the study, the peak value, RMS, magnitude and spectral partition sum are selected as degradation characteristics of the bearing. Among them, the peak value is the maximum magnitude of the vibration signal, which can reflect the vibration intensity of the bearing, and its calculation method is expressed as

$$X_P = \max |x_i| \tag{3.1}$$

In Eq. (3.1), X_P represents the peak value, and x_i represents the input eigenvector, where $i = 1, 2, \ldots, N$. The RMS value of the vibration signal can reflect the vibration energy of the bearing, and is calculated as

$$X_R = \sqrt{\frac{1}{N}\sum_{i=1}^{n} x_i^2} \tag{3.2}$$

In Eq. (3.2), X_R indicates the RMS of the vibration signal, and N indicates the total amount of data in the sample. Sharpness of the vibration signal reflects the vibration frequency distribution of the bearing, and its calculation method is

$$X_K = \frac{1}{N}\frac{1}{X_R^4}\sum_{i=1}^{N}(|x_i - \overline{x}|)^4 \tag{3.3}$$

In Eq. (3.3), X_K represents the craggy index, and $\overline{x}$ represents the average value of the input eigenvectors. Spectral partitioning and summation is to divide the vibration signal spectrum into several intervals and calculate the sum of spectral energy in each interval, which can reflect the spectral distribution of the bearing vibration signal, and its calculation method is

$$X_F = \sum_{k=[V+N_\eta(r-1)]/V}^{N_\eta v/V} S(r) \tag{3.4}$$

In Eq. (3.4), X_F denotes the value of the sum of spectral partitions, which is a one-dimensional vector containing M elements, N_η denotes length of the signal spectrum, r means the amount of spectral lines in each spectrum, and $m = 1, 2, \ldots, M$. In the next step, data preprocessing is performed on the acquired feature parameters to raise the learning efficiency of the network and to prevent the occurrence of the gradient vanishing problem. That is, the data are standardized and normalized, and the calculation method is indicated by

$$o' = \frac{o - u}{\sigma} \qquad o'' = \text{round}\Big(\frac{o' - o_{min}}{o_{max} - o_{min}}\Big) \tag{3.5}$$

In Eq. (3.5), o denotes the collected data, o' denotes the normalized data, u means the mean value of all the data, σ refers to the standard deviation of all the data, o'' denotes the normalized data, which is dimensionless with the range of $[0, 1]$, o_{min} denotes the rounding function, o_{min} means the minimum value of the data, and o_{max} expresses the maximum value of the data. In summary, the peak value, RMS, craggyness and spectral partition summation can effectively reflect the performance degradation state, so they are selected as the degradation characterization indexes of the bearings.

3.2. DNN-based bearing life prediction model construction

With continuous growth of artificial intelligence technology, deep learning algorithms, as powerful tools, they have shown great potential in the field of bearing life prediction for electromechanical equipment (Bhosle and Musande, 2023). The study chooses DNN model to perform bearings life prediction based on the characteristic indicators of bearing life degradation. DNN consists of multiple layers of neurons, each with connections to adjacent layers, and can be used to handle complex nonlinear problems. It has been widely used in fields such as image and speech recognition, natural language processing, and recommendation systems. The DNN model architecture is shown in Fig. 2.

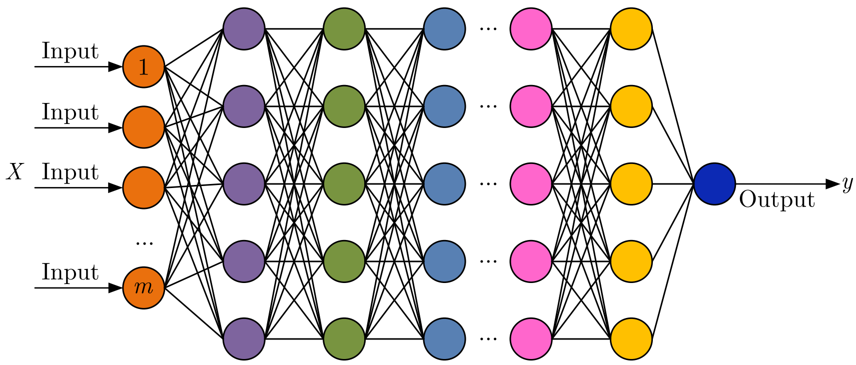

Fig. 2. DNN model architecture

The network structure of DNN is a typical deep learning model, which is composed of an inputting layer, multiple hidden layers and an outputting layer. The inputting layer is responsible for receiving m-dimensional input data and passing it to the next layer by linear transformation through an activation function. Repeating this process until the outputting layer is reached, the final outputting is obtained. The number of network layers of a DNN can vary depending on the application scenario, and some complex models can even reach 20 layers or more. This multi-layer structure can better capture complex features of the data and thus predict results more accurately. When training bearings using DNNs, the study first initializes all parameters by a random normal distribution, then uses the ReLu function in the middle layer of the network and the Sigmoid function in the last layer to better match the normalized data. In terms of the loss function, an expression is shown as

$$F_M = \frac{1}{N}\sum_{i=1}^{N}(y_e^i - y_p^i)^2 \tag{3.6}$$

In Eq. (3.6), F_M represents the loss function, y_e^i represents the experimental value, and y_p^i represents the predicted value. The next step is to use the Adam function for optimization and train the DNN using the learning rate decay mechanism. The Adam optimizer is an optimization algorithm with an adaptive learning rate, which combines the advantages of momentum gradient descent and adaptive learning rate, and can adjust the learning rate of each parameter with the first-order and second-order moment estimation of the gradient, so as to optimize the model parameters effectively. When training the DNN, due to complexity of the network structure and uncertainty of the data, one needs to optimize the model performance by adjusting the learning rate, and the learning rate decay mechanism is able to raise the generalization ability and stability of the DNN model by gradually decreasing the learning rate, which is computed as

$$l_r = l_r(min) + [l_r(max) - l_r(min)]\mathrm{e}^{-\frac{itr}{d}} \tag{3.7}$$

In Eq. (3.7), l_r represents the learning rate. $l_r(max)$ and $l_r(min)$ mean the maximum and the minimum values of the learning rate, respectively. itr refers to the amount of iterations, and d represents the decay rate of the learning rate. After setting the parameters, the degradation characteristics are used as inputs to obtain the degradation trend of the bearing, and finally the remaining life of the bearing can be calculated by obtaining the moment of bearing failure according to the failure threshold, which is shown as

$$t_r = \{t' - t | t' > t, Z(t)\} \tag{3.8}$$

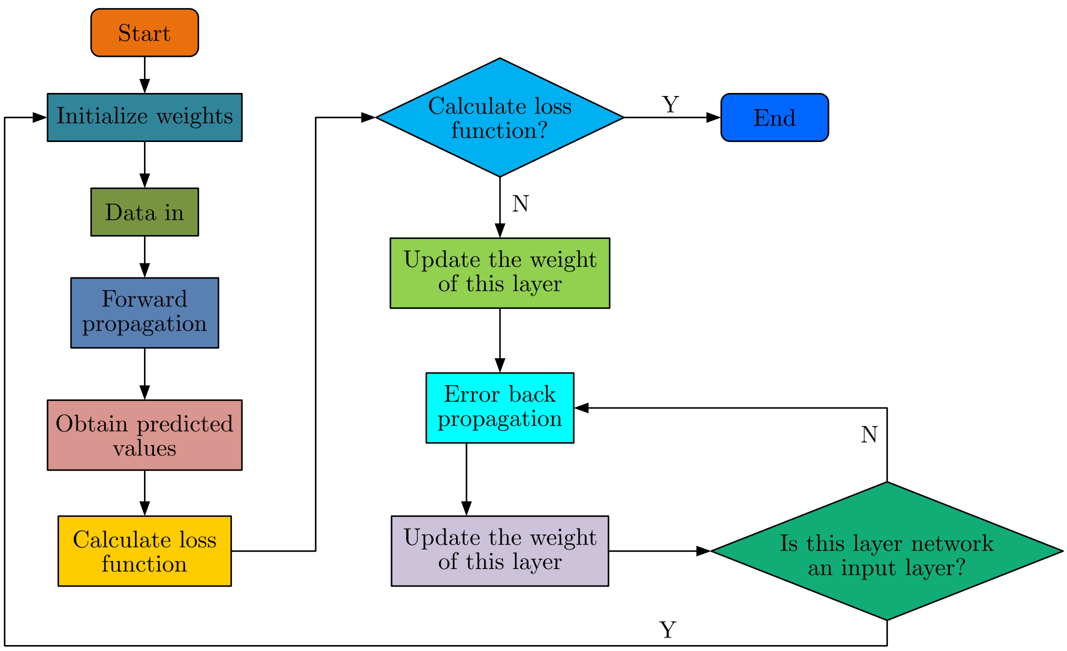

Fig. 3. DNN based bearing life prediction process

In Eq. (3.8), t_r represents the remaining life of bearing, t' represents the moment of failure, t represents the current operating moment of the bearing, and $Z(t)$ represents all historical operating conditions of the bearing up to the current moment. The bearing life prediction process based on the DNN is shown in Fig. 3.

Firstly, the data preprocessing is performed to normalize life vibration signals of the original bearings and label them with health indicators, as well as the ash content training and testing sets. Then a DNN model is built, hyperparameters initialized, and the processed data input into the DNN model. Finally, based on the loss value, the weights, biases, and other parameters of each convolutional layer in the network are updated and optimized to achieve the optimal model, thereby obtaining the bearing health index construction model.

3.3. An improved bearing life prediction model based on DNN-KNN

Although the bearing life prediction model for electromechanical equipment has been built on the basis of DNN, the DNN cannot accurately describe all structural details of the complex mapping function, which leads to a certain deviation of the prediction output from the real data and is prone to local optimal solutions. And the KNN is a local model, which is good at dealing with nonlinear decision boundary and multi-classification problems (Althubaiti *et al.*, 2022). Therefore, it is studied to combine the DNN and KNN into a DNN-KNN model to correct the deviation value in prediction and raise the effectiveness of the model. The bearing life prediction process based on the DNN-KNN model is shown in Fig. 4.

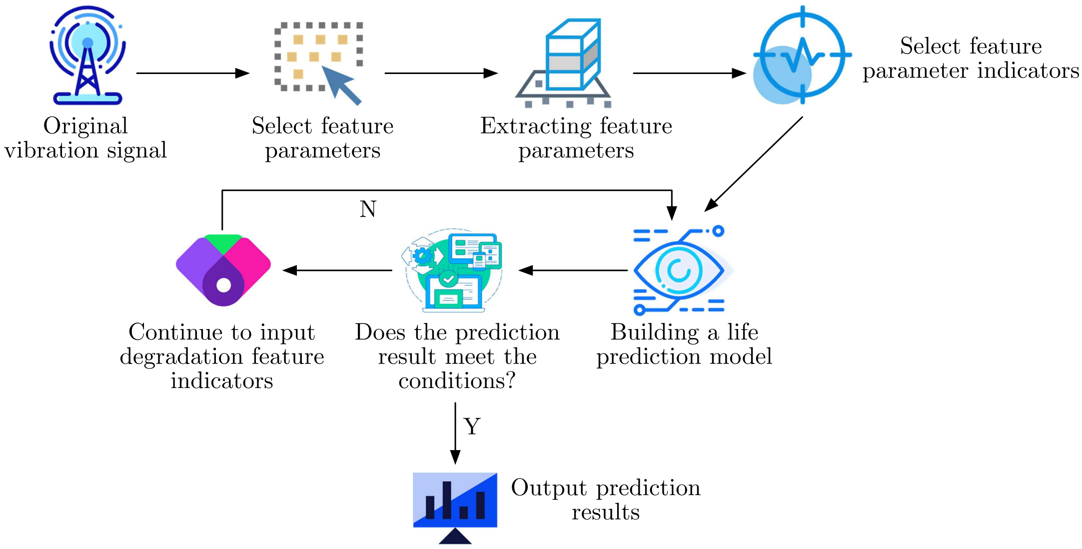

Fig. 4. Bearing life prediction based on DNN-KNN model

For bearing life prediction, the original vibration signals need to be input, and the feature parameters of the signals are extracted from them, which include frequency-domain features, time-domain features, and time-frequency-domain features. For any bearing, it is difficult for a single DNN model to describe the relationship between all feature parameters and bearing life. Therefore, the study first clusters multiple DNN models expressioned in a vector form

$$\mathbf{DNN}_m = \begin{bmatrix} DNN_1 \\ DNN_2 \\ \vdots \\ DNN_m \end{bmatrix} \tag{3.9}$$

In Eq. (3.9), $\mathbf{DNN}_m$ represents the set of m DNN models. Multiplying the input feature vectors with the clustering results of multiple DNN models, ome is able to obtain a set of vectors of the output predicted values, which is calculated as

$$\mathbf{x}_i \times \mathbf{DNN}_m = \begin{bmatrix} P_1^i \\ \vdots \\ P_j^i \\ \vdots \\ P_m^i \end{bmatrix} \tag{3.10}$$

In Eq. (3.10), P_M^i represents the first i m predicted value. At this point, the average of predicted values is generally calculated as the final result, and the calculation is denoted by

$$\overline{P} = \frac{1}{m} \sum_{j=1,m} P_j^i \tag{3.11}$$

In Eq. (3.11), $\overline{P}$ denotes the average prediction value. But the results calculated in this way ignore the prediction bias of each DNN model. Therefore, the study introduces a KNN algorithm by which the test data are predicted, which usually predicts the values of new input samples by analyzing the training samples. Specifically, the KNN algorithm selects a number of training samples to generate the nearest-neighbor dataset, and the KNN algorithm clusters the scatter points as shown in Fig. 5.

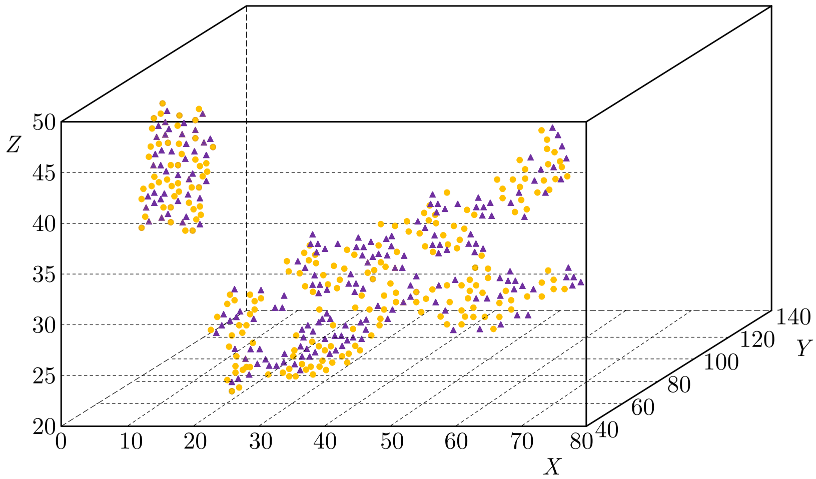

Fig. 5. KNN algorithm clustering a scatter plot

In Fig. 5, the KNN algorithm is able to find the nearest neighbors by calculating the distance between sample points and using the information from these neighbors to classify or regressively predict new data points. The algorithm has advantages of simplicity, being easy to understand and implement, and is suitable for small datasets and sample imbalance. The training dataset is first set to be $T = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, where each sample contains an input feature vector $\mathbf{x}$ and a corresponding output prediction $\mathbf{y}$. The set expression is shown as

$$Y_K = \{y_i : \quad i = 1, 2, \ldots, k\} \tag{3.12}$$

In Eq. (3.12), Y_K denotes the nearest-neighbor dataset, and i expresses the i-th sample. In the next step, the predicted values of test samples can be calculated from these similar training samples with the fokkowing expression

$$Y_{PV} = \frac{\sum_{i=1}^{k} w_i x_i}{\sum_{i=1}^{k} w_i} \qquad i = 1, 2, \ldots, k \tag{3.13}$$

In Eq. (3.13), Y_{PV} means the test value of the test sample, and w_i indicates the weights of the approximation sample. These weights can be determined based on the similarity with the test sample, and the inverse of the distance is usually used as the weight. The next step is to calculate the input prediction value from the test value of the test sample, which is worked out and expressed by

$$P(x) = \frac{1}{k} \sum_{j \in N_k(x)} y(x_j) \tag{3.14}$$

In Eq. (3.14), $P(x)$ denotes the predicted value of the input feature vector $\mathbf{x}$, $N_k(x)$ denotes the set of k data similar to the feature vector $\mathbf{x}$, and $y(x_j)$ denotes the true value corresponding to the data x_j. The next step is to calculate the similarity between the predicted values of the test and training samples by using Pearson's correlation coefficient to correct the bias between the two, and the expression of Pearson's correlation coefficient is shown as

$$R(\alpha, \beta) = \frac{\sum_i (\alpha_i - \overline{\alpha})(\beta_i - \overline{\beta})}{\sqrt{\sum_i (\alpha_i - \overline{\alpha})^2} \sqrt{\sum_i (\beta_i - \overline{\beta})^2}} \tag{3.15}$$

In Eq. (3.15), R denotes the Pearson correlation coefficient, and α and β denote the two eigenvectors. The correction for bias is calculated from the equation

$$P'(x) = P(x) + \frac{1}{k} \sum_{j \in N_k(x_i)} [y(x_j) - P(x)] \tag{3.16}$$

In Eq. (2.16), $P'(x)$ denotes the real value, and $y(x_j) - P(x)$ denotes the deviation of the predicted value. At this point, the improvement of bearing life prediction on the basis of DNN is completed.

4. Analysis of the results of the DNN-KNN-based bearing life prediction model for electromechanical equipment

This Section focuses on the research findings of the designed fusion bearing life prediction model, with the first section analyzing the performance of the designed model and the second section analyzing the effectiveness of the designed model in practical applications.

4.1. Performance analysis of the bearing life prediction model based on DNN-KNN

To verify the performance of the designed DNN-KNN-based bearing life prediction model for electromechanical equipment, the study sets the size of convolution kernel to 5×5, sets the learning rate to 0.0001, and the iteration times to 200. At the same time, let the number of hidden layers in the network be 8, with the number of neurons in each layer being 300, 2001, 150, 100, 80, 50, 30, 1, and the last layer being the output layer. Since each input data outputs a predicted lifespan value, the output layer contains 1 neuron. Firstly, the accuracy and loss of the designed model are calculated and compared with the DNN, Support Vector Machines, and Decision Tree algorithms. The results are shown in Fig. 6.

From Fig. 6a, the accuracy of all four algorithms tended to increase as the amount of iterations increased. Among them, the accuracy of the designed DNN-KNN algorithm is 0.96 when it tends to level off, the accuracy of the DNN algorithm is 0.90 when it tends to stabilize, the accuracy of the SVM algorithm is 0.87 when it reaches stability, and the accuracy of the DT algorithm is 0.81 when it tends to stabilize. From Fig. 6b, the loss value of the four algorithms had a tendency to decrease gradually, and the four algorithms reached the maximum amount of iterations. The loss values when the four algorithms reached the max amount of iterations are

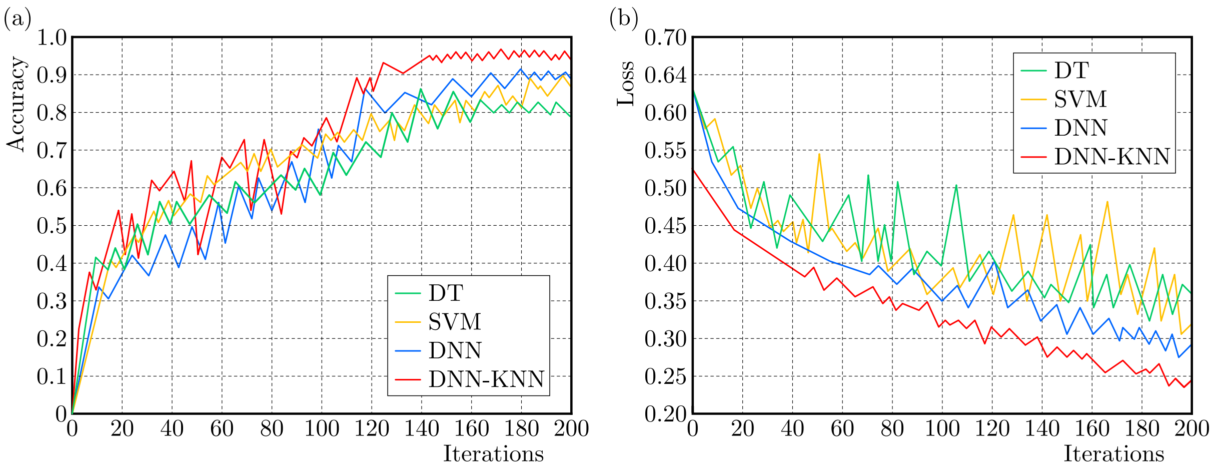

Fig. 6. Accuracy and loss of different models

0.23, 0.29, 0.32, and 0.35, respectively. The above outcomes denoted that the designed DNN-KNN algorithm has a high prediction accuracy and good convergence performance. In the next step, the acquired dataset is divided into six types of test sets, and the errors of different models are calculated separately. The outcomes are expressed in Table 1.

Table 1. Errors of different models

	DNN-KNN	DNN	SVM	DT
Test set 1	14.16	12.56	27.51	17.55
Test set 2	21.69	29.54	22.32	23.47
Test set 3	16.33	20.21	18.18	20.06
Test set 4	0.93	10.43	6.09	15.49
Test set 5	24.25	10.59	18.02	26.87
Test set 6	14.62	21.12	26.13	28.32
Average error	15.33	17.41	19.71	21.96

From Table 1, the average error of the designed DNN-KNN based life prediction model is 15.33%, the average error of the DNN-based model is 17.41%, and the average errors of the two prediction models, SVM and DT, are 19.71% and 21.96%, respectively. The error of the research-designed life prediction model based on the DNN-KNN is significantly lower than that of the other algorithms. The findings further demonstrated the high prediction accuracy of the designed model and also prove its reliability. Finally, the recall and $F1$ value are introduced to assess the comprehensive effectiveness of the designed algorithm and compared with the other four algorithms. The results are shown in Fig. 7.

In Fig. 7a, the recall of all four models tends to increase and level off as the iteration times increased. Among them, the recall of the designed DNN-KNN model is 97% when it reaches plateau, and the recall of the three models, DNN, SVM, and DT, are 93%, 88%, and 85% when they plateau, respectively. From Fig. 7b, the $F1$-score of all four models gradually increased as the iteration times increased. When the maximum amount of iterations was reached, the $F1$-score of DNN-KNN, DNN, SVM, and DT were 0.93, 0.80, 0.78, and 0.72, respectively. It can be found that the recall and $F1$-score of the designed DNN-KNN model are significantly higher than those of the other models, indicating that it possesses a better comprehensive performance, and meanwhile, proving that it has a good generalization ability.

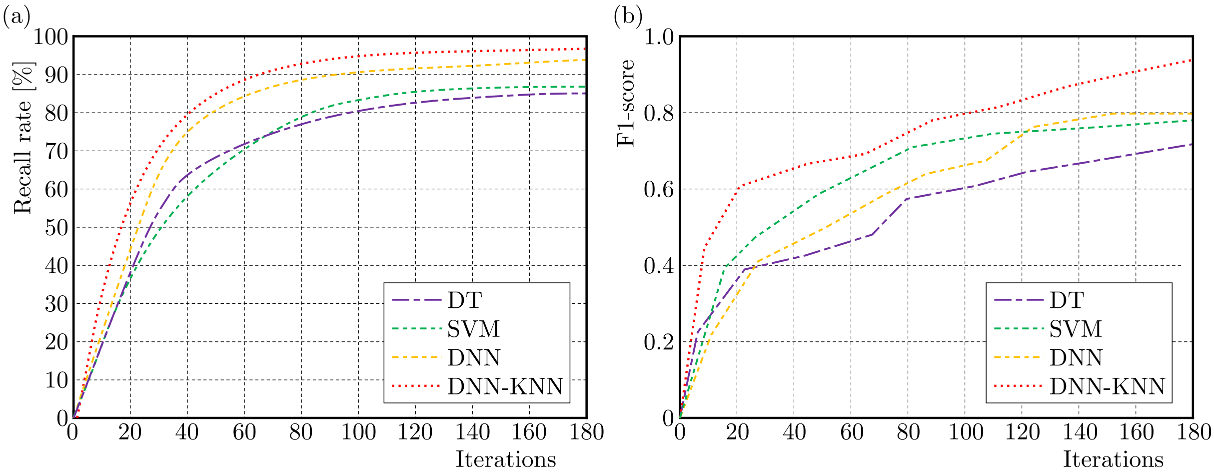

Fig. 7. Recall rates and $F1$-score of different algorithms

4.2. Analysis of the effect of practical application of the life prediction model based on DNN-KNN

To assess the performance of the designed DNN-KNN-based life prediction model for bearings in electromechanical equipment in practical applications, the study firstly selects the test bearings, and then calculates the residual life of the bearings using the DNN-KNN-based and DNN-based life prediction model, respectively. The scatter plots of the predicted life are shown in Fig. 8.

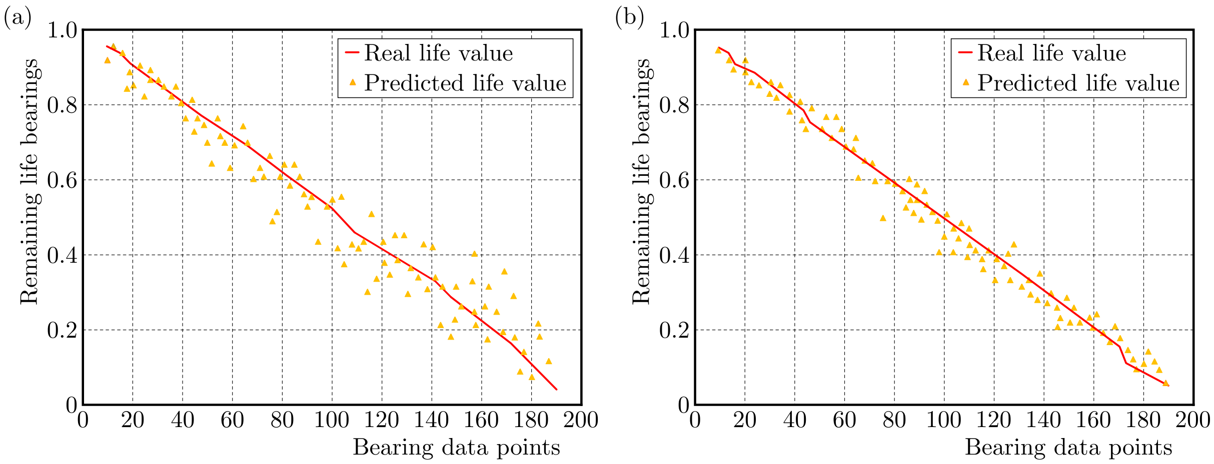

Fig. 8. Scatter plots of the residual life of test bearings based on different algorithms

In Fig. 8, among the two bearing residual life prediction models, the remaining life prediction value of the DNN-KNN-based model is obviously closer to the real life value, indicating that the prediction accuracy of the designed model is higher. In the next step of the study, six test bearings are selected, and the feature indexes are selected by different methods. The curves of the average value of degradation feature indexes obtained by each algorithm are compared with the cycle, and the findings are indicated in Fig. 9.

In Fig. 9, the values of degradation feature indicators extracted by both algorithms are between 0 and 1, which is conducive to determining the range of the indicator failure threshold. However, the curve of the mean feature data extracted by the DNN-KNN-based residual life prediction model is obviously smoother and less fluctuating, which proves that it has better stability and reliability in extracting feature indicators. This implies that the DNN-KNN-based

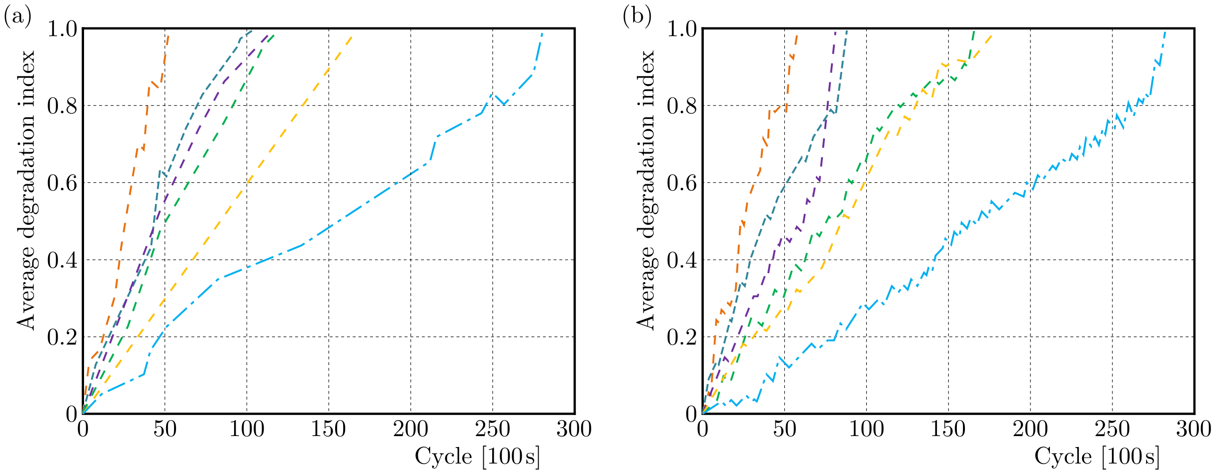

Fig. 9. The curve of the average value of degradation characteristic indicators changing with the cycle

model can more accurately capture the bearing degradation trend and provides more reliable life prediction results. The next step of the study introduces robustness and correlation to further evidence the effectiveness of the designed remaining life prediction model, and, at the same time, compares the results with those of the DNN-based residual life prediction model, which are given in Table 2.

Table 2. Comparison of robustness and correlation between different models

Testing bearings	DNN-KNN		DNN	
	Robustness	Correlation	Robustness	Correlation
Bearing 1	0.98	0.98	0.97	0.95
Bearing 2	0.98	0.99	0.98	0.96
Bearing 3	0.99	0.98	0.96	0.97
Bearing 4	0.98	0.98	0.98	0.98
Bearing 5	0.99	0.99	0.97	0.90
Bearing 6	0.99	0.99	0.92	0.94

From Table 2, among the six test bearings, the average robustness and average correlation of the DNN-KNN-based remaining life prediction model are 0.985 and 0.985, respectively, and the mean values of the robustness and correlation of the DNN-based remaining life prediction model are 0.963 and 0.95, respectively. The above findings indicated that the DNN-KNN-based remaining life prediction model performs better in terms of robustness and correlation. Finally, the study introduces the mean absolute error (MAE), mean square error (MSE), and RMS error to evaluate the prediction results, and compares the results with those of the DNN-based prediction model and the SVM-based prediction model. The results are shown in Fig. 10.

In Fig. 10, the MAE, MSE and RMS error of the SVM-based remaining life prediction model are 0.036, 0.071 and 0.039, respectively, and the values of the three indicators of the DNN-based remaining life prediction model are 0.024, 0.073 and 0.043, respectively, whereas the values of the three indicators of the designed DNN-KNN-based remaining life prediction model are 0.019, 0.066 and 0.025, respectively. It can be found that the three indicators of the designed model are significantly lower than the other models, which further proves that the prediction accuracy of the designed model is higher. The indicator values are 0.019, 0.066, and 0.025, respectively. To further verify the superiority of the DNN-KNN based electromechanical equipment bearing life prediction model, the average absolute percentage error and maximum absolute error were introduced to calculate the two indicator values of the design method and compared with the

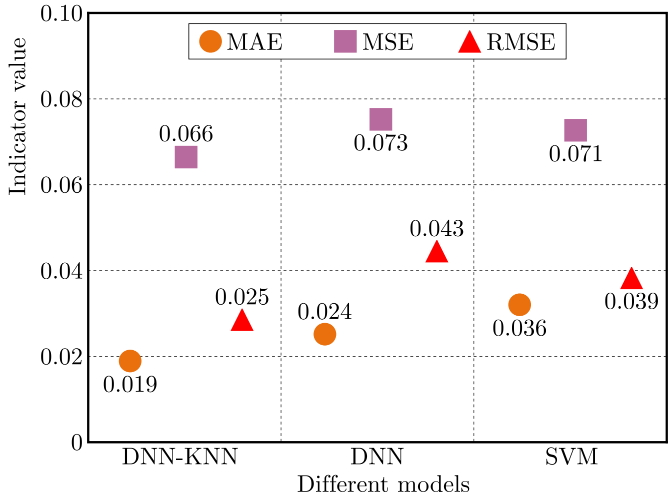

Fig. 10. Indicator values for different models

two indicator values of the latest methods in (Nistane, 2024; Li and Wang, 2024; Fei *et al.*, 2024; Yang *et al.*, 2024). The results are shown in Table 3.

Table 3. Comparison of average absolute percentage error and maximum absolute error of five methods

Model	Maximum absolute error	Maximum absolute percent error
Nistane (2024)	0.0967	0.1223
Li and Wang (2024)	0.1046	0.0955
Fei *et al.* (2024)	0.0953	0.0837
Yang *et al.* (2024)	0.0988	0.0846
DNN-KNN	0.0920	0.0732

From Table 3, it can be seen that the maximum absolute error and average absolute percentage error of the designed DNN-KNN model are 0.0920 and 0.0732, respectively. Their maximum absolute errors are 0.0047, 0.0079, 0.0033, and 0.0068 lower than those in (Nistane, 2024; Li and Wang, 2024; Fei *et al.*, 2024; Yang *et al.*, 2024), respectively. Its average absolute percentage errors are 0.0491, 0.0223, 0.0105, and 0.0114 lower than the other four methods, respectively. It can be found that the prediction error of DNN-KNN is smaller than in other methods, which proves that it can effectively improve the accuracy of predicting the remaining life of bearings.

5. Conclusion

In the field of engineering, accurate remaining life prediction of bearings in electromechanical equipment is of crucial significance for the reliability analysis and maintenance of the equipment. The traditional prediction methods are often difficult to meet the accuracy and real-time demands in the complex engineering environment. Therefore, the study firstly carries out selection of indicators of bearing degradation, then introduces DNN, constructs a remaining life prediction model based on these indicators, and finally introduces KNN to correct the deviation of the DNN model, and designs a DNN-KNN residual life prediction model. The results show that in the accuracy and loss calculation, the accuracy of the four algorithms when reaching the maximum number of iterations is 0.96, 0.90, 0.97, and 0.81, respectively, which means that the prediction accuracy of the designed algorithms is high. In the error calculation of different models, the average errors of the four models are 15.33%, 17.41%, 19.71% and 21.96%, respectively, which further proves that the prediction accuracy of the proposed models is high and demonstrates their reliability. In the recall and $F1$ value calculations of different models, the designed DNN-KNN-based lifetime prediction model has a recall and $F1$ value of 97% and 0.93, respectively, which are significantly higher than in the other models, proving that it has a better overall performance, and also proving that it has a better generalization ability. The above findings prove the effectiveness of the designed life prediction model based on DNN-KNN, but the study still has some shortcomings when making predictions. A large number of historical data of bearings are used, which may have a certain impact in terms of computational efficiency, and the subsequent will continue to be improved in this aspect.

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